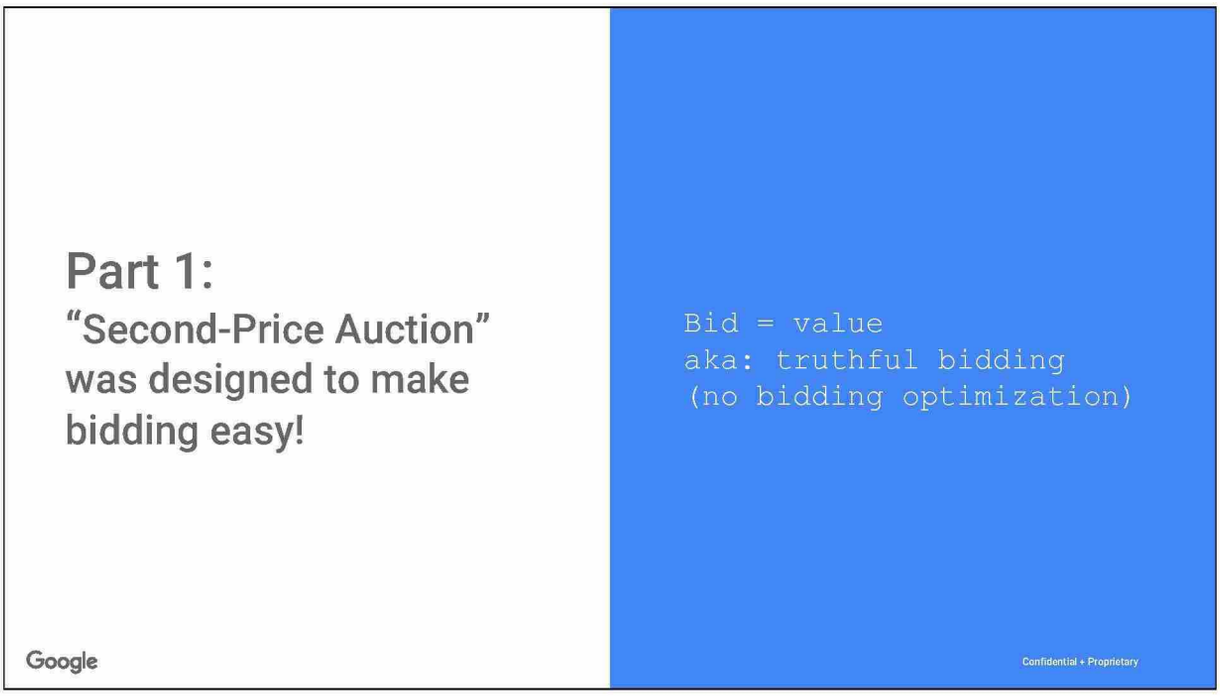
Control Number :	GOOG-DOJ-AT-00088452
All Custodians :	Ali Nasiri Amini
Custodian :	Ali Nasiri Amini
Date/Time Created :	10/30/2019 8:34 PM
Date/Time Sent :	
MODIFICATION DATE :	10/30/2019 10:07 PM
File Name :	auction ..._1uMTEVII9HYlwLkkmQd3EOw -_9ucZ6uwKBlFF71tjWig.pptx


Part 1:
“Second-Price Auction” was designed to make bidding easy!
Google
Bid = value
aka: truthful bidding
(no bidding optimization)
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Second-Price Auctions and "truthful" bidding

If an advertiser **knows** the value of a click/impression to himself,

then in **a second-price** auction, he should just bid this value.

→ Bidding is trivial (no optimization needed)

- Well-celebrated theory.
- Served as a cornerstone of Google's ad model success in early days.
- Simplifies advertiser problem: Just tell us the value of a click to you.

Google

Part 2:
Uncertainty in value

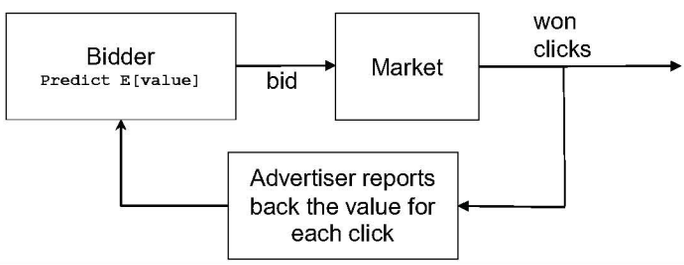
Advertiser: But all clicks are not equal to me, I don't know the value of a click before auction but if I win I can measure it!

Google

Significant heterogeneity in value of clicks especially in display ads.

How uncertainty in value impacts bidding?

1. Bidding the expected value, **"Truthful bidding"**, is not optimal!
2. It is hard to predict due to **"censored"** training data:
   Observed data is biased! We only observe value of clicks that we won, but we need to predict the value of queries that we are competing for.



Google

Confidential + Proprietary

Most of

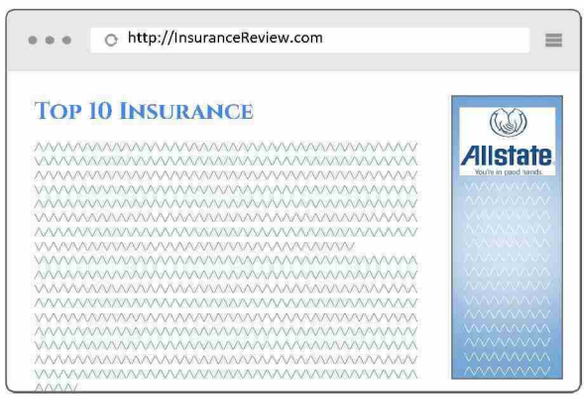
Hidden information of competition

Allstate and Geico are competing on http://InsuranceReview.com.
Geico bids higher for users that already visited its website (Remarketing).

Allstate bids $1 cpc but sees:

- For 10% of clicks:
  - cpc = $0.95
  - avg(value) = $2
- For 90% of clicks
  - cpc = $0.5
  - avg(value) = $0.89

avg value over all clicks = $1



Google

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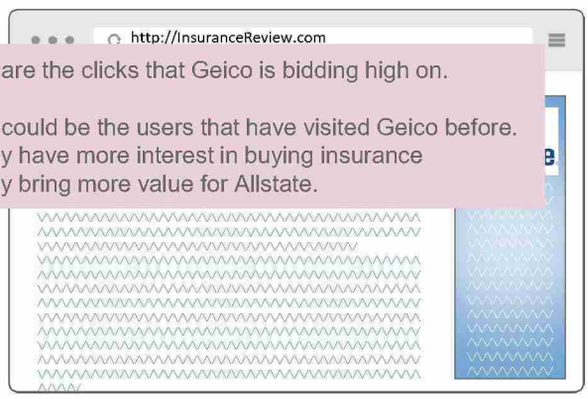

Google

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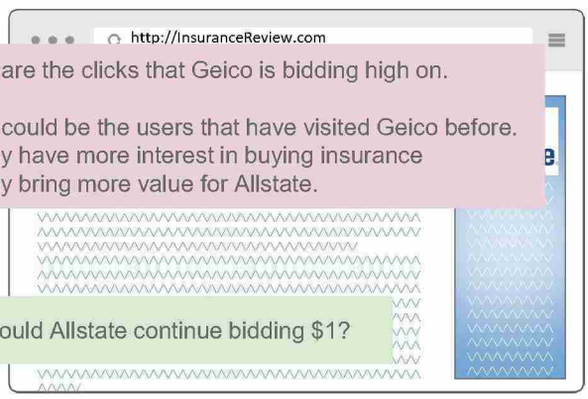

These are the clicks that Geico is bidding high on.

These could be the users that have visited Geico before.
→ They have more interest in buying insurance
→ They bring more value for Allstate.

Should Allstate continue bidding $1?

Google

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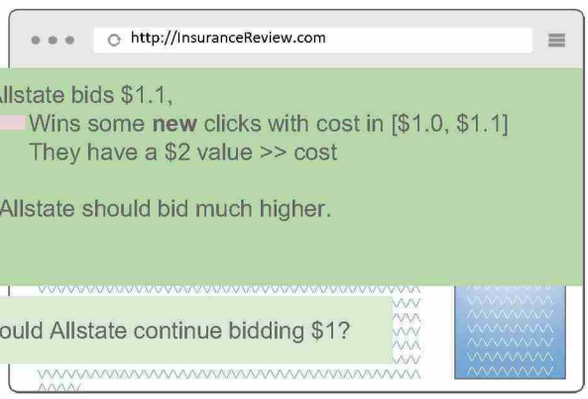
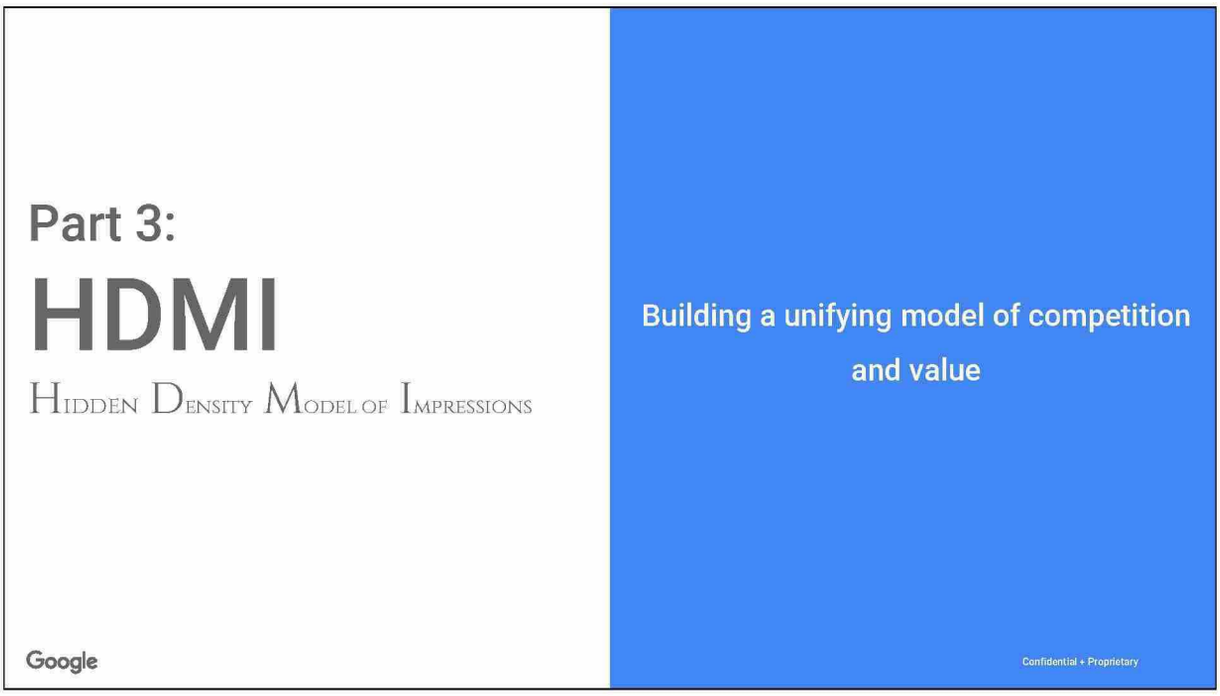


Google


Part 3:
HDMI
Hidden Density Model of Impressions
Google
Building a unifying model of competition and value
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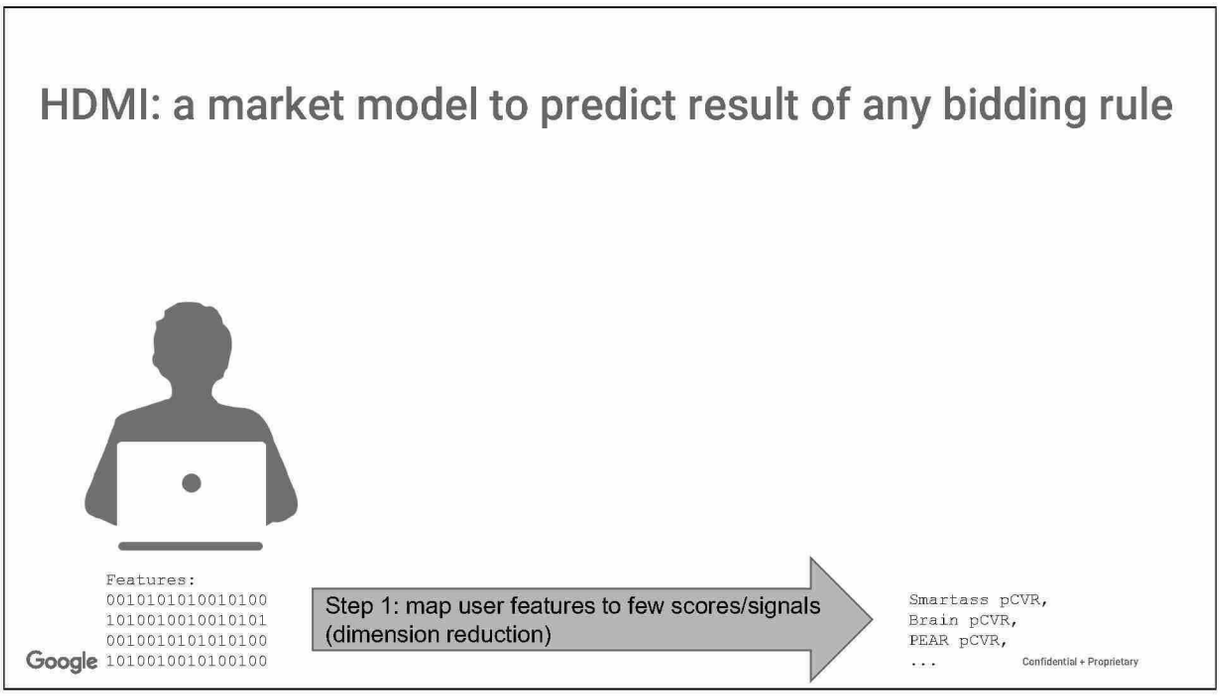
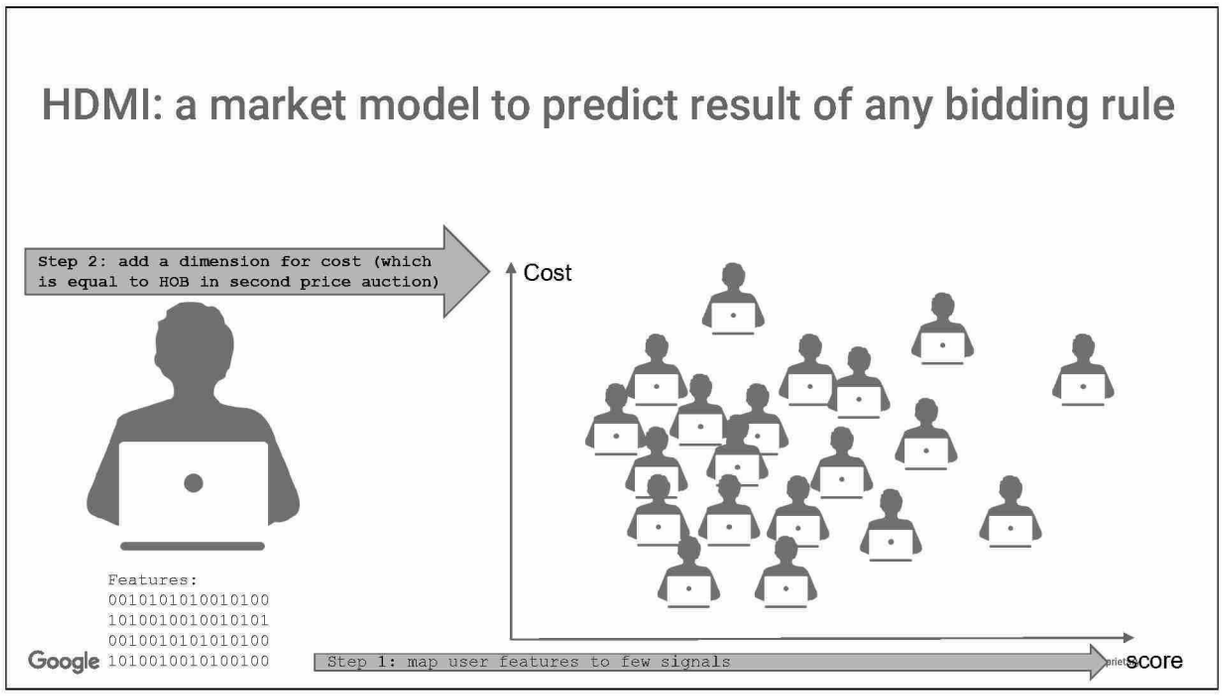
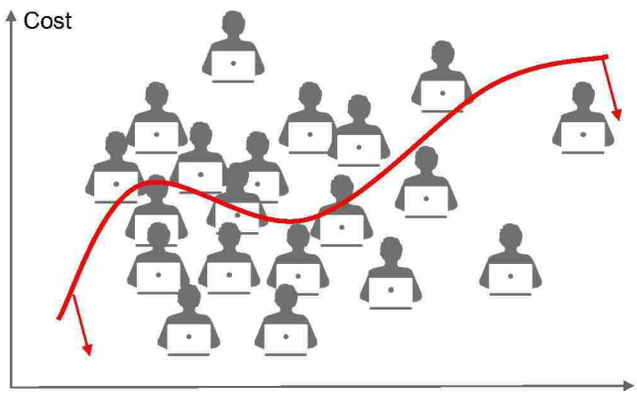

HDMI: a market model to predict result of any bidding rule
Features:
0010101010010100
1010010010010101
0010010101010100
1010010010100100
Google
Step 1: map user features to few scores/signals (dimension reduction)
Smartass pCVR,
Brain pCVR,
PEAR pCVR,
...
Confidential + Proprietary


HDMI: a market model to predict result of any bidding rule
Step 2: add a dimension for cost (which is equal to HOB in second price auction)
Cost
Features:
0010101010010100
1010010010010101
0010010101010100
1010010010100100
Google
Step 1: map user features to few signals
score

HDMI: a market model to predict result of any bidding rule

- Any bidding rule draws a hypersurface that separates the space to “won” vs “lost”.
- The goal of the bidding optimization is to separate in a way that we win all users with
  E[Value - Cost] >0



Google

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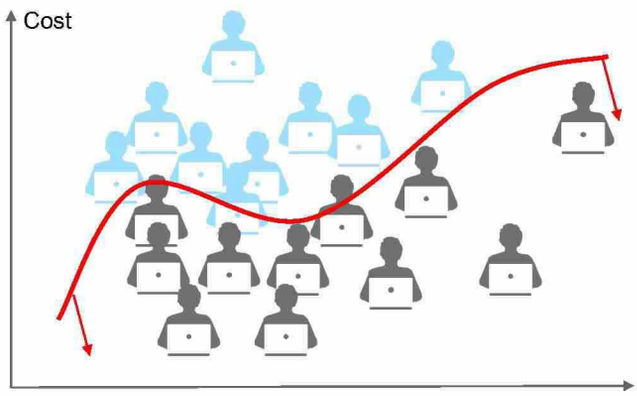
HDMI: a market model to predict result of any bidding rule

- **Challenge:** Build a model for market from partial biased data as buyer often has only access only to whatever he won in the past.
- HDMI recognizes this limitation in data and does appropriate correction.



Google

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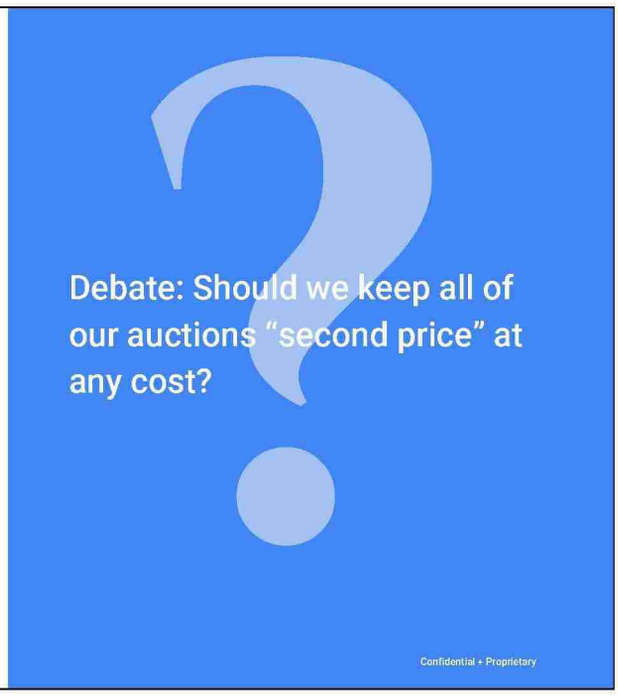
Part 4:
So “Second price” does not necessarily make the bidding easy

Google



Observation: auction discount is much higher on Google Second-price auctions

Exchange	Auction discount = cost / bid
AdX	34%
AdSense	40%
External Exchange	11%

We can not audit the code but we can run experiments to lower the bid on a small fraction of users and see what happens?

Google

Project Poirot

- **Detective Part:** Poirot explores the auction space using multiple experiments with various z values.
- Experiment data will be fed into a ML to learn how surplus varies vs bid multiplier in various segment of inventory

$$surplus = \sum_{imp\ i} (value_i - payout_i)$$

- **Judicial Part:** Poirot acts as a fair judge an adjusts the advertiser's bid in order to maximize surplus

Google

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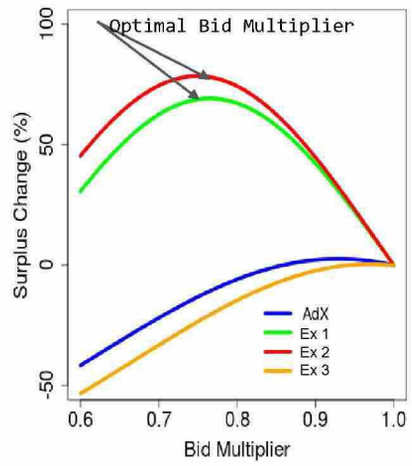
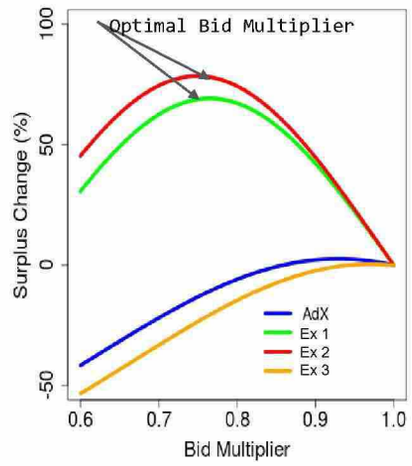
Result:

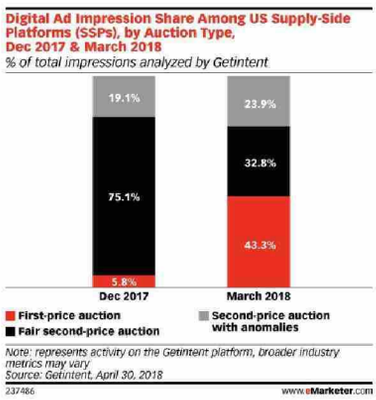


Google

Result:



Market shift to first price



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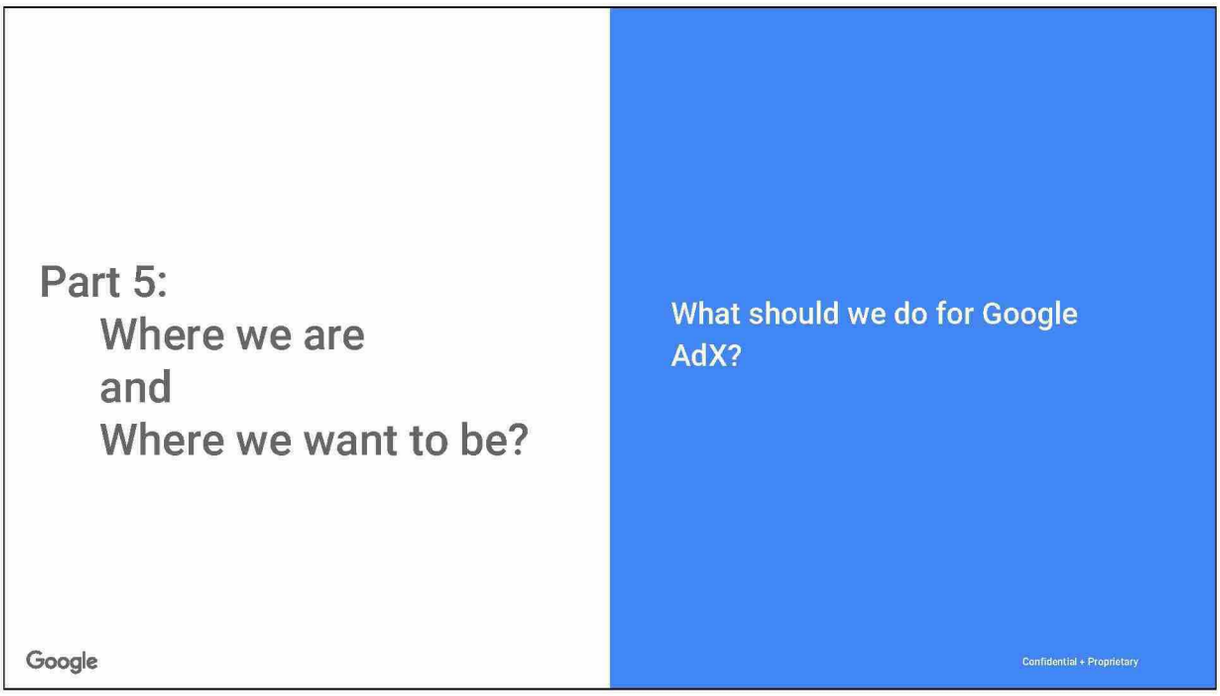
Part 5:
Where we are
and
Where we want to be?
Google
What should we do for Google AdX?
Confidential + Proprietary

Where we are

- We started with the second-price auction to make bidding truthful and easy!
- Even with second-price auction bidding is not trivial. (Bidder should actively model the market).
- Second price auctions is not verifiable. (Unless audit the code!).
- The rest of the market is shifting to the first price auction.

Google

Where we will be

- **Transparent first-price auction:** Highest bidder wins and pays her own bid. But the winner gets to know what the second highest bid was.
- **Advantage:** No need for bid-lowering experiments for price discovery.
- At Google we are converging to this solution as a step forward but we have not seen all the episodes of this show!

Google


Appendix
Google
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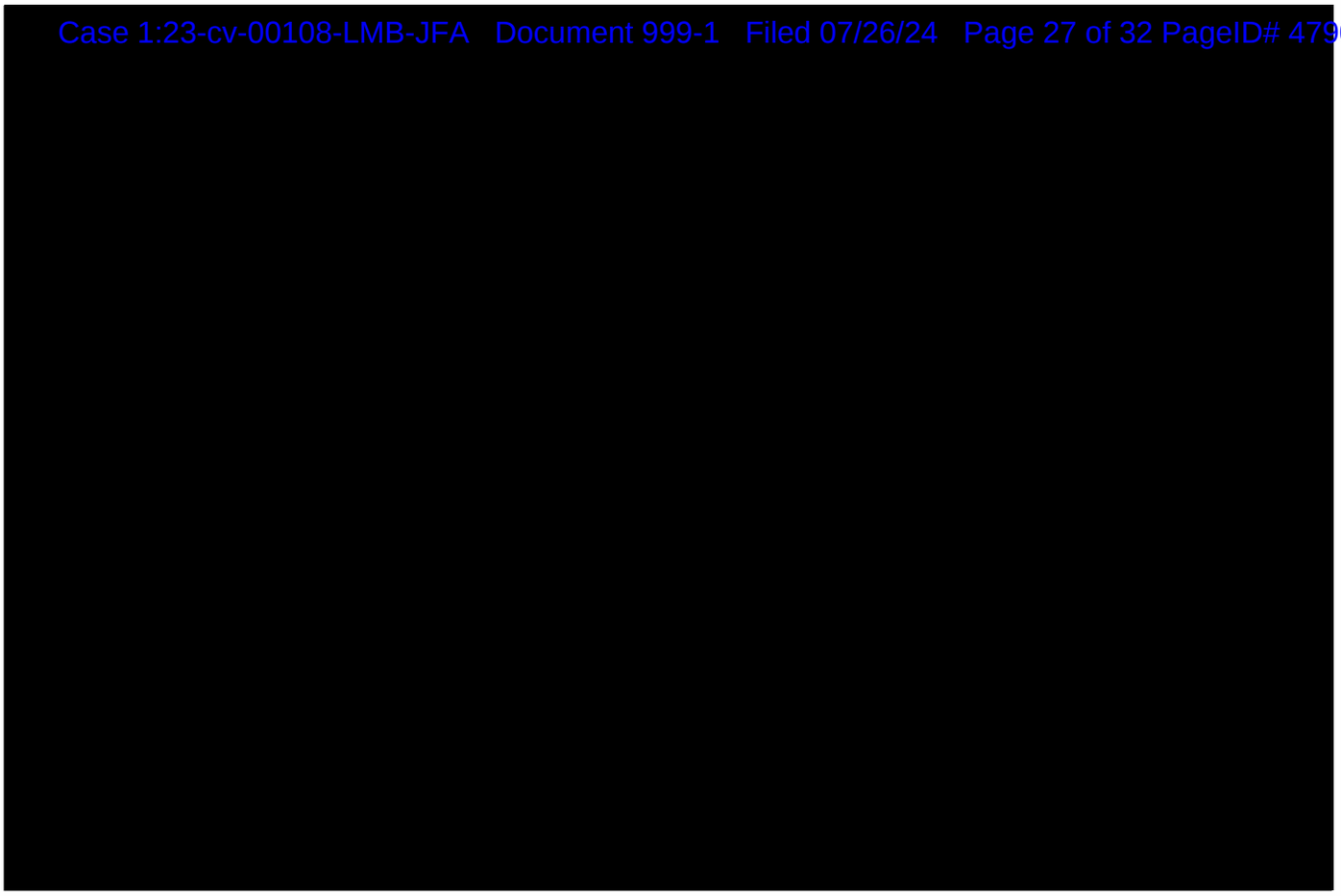


More: search for HDMI on Moma

$$
\begin{aligned}
L &= E\{e_{n+1}|s_{n+1}, d_n^W\} + \lambda E\{c_{n+1} - T_p e_{n+1}|s_{n+1}, d_n^W\} \\
&= \int_0^{\infty} \int_0^{b=h(s)} k s^{a_{(p|s,c),1}} c^{a_{(p|s,c),2}} f(c|s) f(s) dc\, ds \\
&+ \int_0^{\infty} \int_0^{b=h(s)} \lambda (c - T_p k s^{a_{(p|s,c),1}} c^{a_{(p|s,c),2}}) f(c|s) f(s) dc\, ds.
\end{aligned}
$$

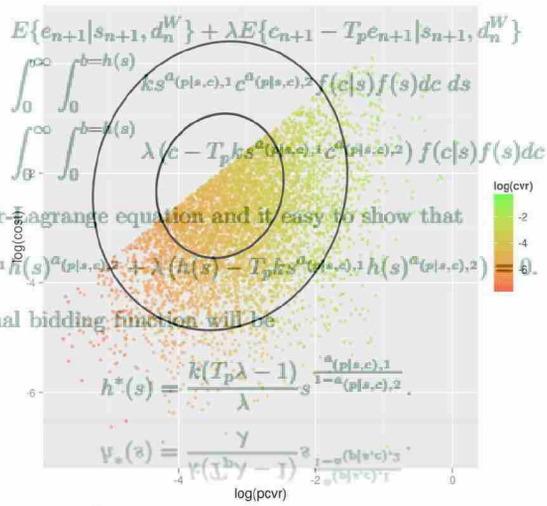
We use Euler-Lagrange equation and it easy to show that

$$k s^{a_{(p|s,c),1}} h(s)^{a_{(p|s,c),2}-1} + \lambda \left(h(s) - T_p k s^{a_{(p|s,c),1}} h(s)^{a_{(p|s,c),2}}\right) = 0. \quad (4.10)$$

So the optimal bidding function will be

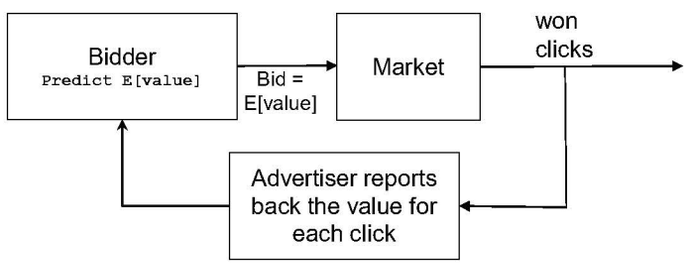
$$h^*(s) = \frac{k(T_p\lambda - 1)}{\lambda} s^{\frac{a_{(p|s,c),1}}{1-a_{(p|s,c),2}}}. \quad (4.11)$$

$$V_*(s) = \frac{\gamma}{\Gamma(1-\gamma)} s^{\frac{1-a_{(p|s,c),1}}{1-a_{(p|s,c),2}}}. \quad (4.11)$$



V1 Solutions

1) Advertiser can compute E[value] from historical data and use that as the bid.
2) E[Value] may vary based on many features.
   Advertisers have access to small subset of them in UI, we has access to a lot more.
1) Tell us the value of past clicks and we build a ML to predict E[value] of future clicks based on a long list of impression features.



Google

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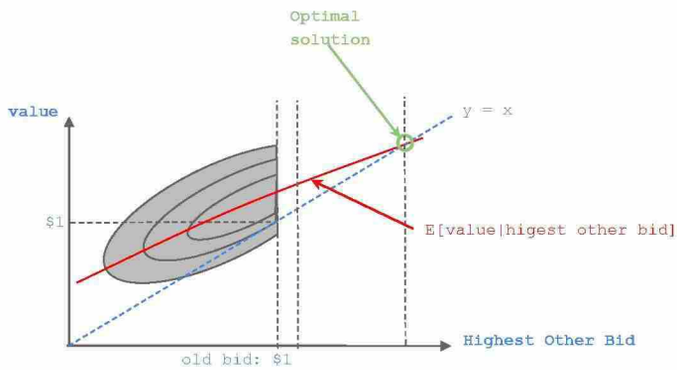
Optimal Bidding in second price auctions

Previous bids = training data

E[value]	Bid	Highest bid	win	value
$1	$1	$0.9	Y	$1.5
$1	$1	$0.2	Y	$0.5
$1	$1	$1.2	N	NA
$1	$1	$1.4	N	NA
...	...			
$1	$1	$0.5	Y	$1.0



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Using information in highest other bid (HOB)

At the time of bidding the HOB is not known, however
we can calculate expected profit margin for different values for HOB.

There is one value for which the advertiser profit would be zero (break-even point).

By submitting this value as the bid, advertiser buy all of queries with positive "expected" margin and loses the auction for all queries for which he has negative expected margin.

HDMI is the system we built for solving such bidding optimization.

Google